

Multi-Sensor Kinematic and Attribute Tracking Using a Bayesian Belief Network Framework

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SUMMARY

Situational awareness plays a major role in many military and civilian operations. Apart from the identity, type, location and dynamics of targets of interest, the situational picture may also provide other target information, such as weapons state, fuel status and intent. Many legacy systems incorporate an automatic tracking capability, with identification, situational assessment and decision-making being left to the operators. The automation of many of these functions is the focus of much research and development.

A necessary prerequisite for updating the state of a target is the correct association of measurements or other information to the track. The ability of Bayesian belief networks (BBNs) to model the uncertain relationships between continuous and discrete variables make them excellent candidates for incorporating both kinematic and attribute information in the association process. A BBN model for a single scan data association problem is presented and used to develop a global nearest neighbours solution using both kinematic and attribute information. Monte Carlo simulations demonstrate the benefit of using attribute information in the association process.

1 INTRODUCTION

Situational awareness plays a major role in many military and civilian operations. The automated situational picture traditionally displayed the position, speed and heading of targets within a region of interest, with the operator manually adding identity and other information. However, modern multi-source algorithms have the potential to automatically update additional target information or attributes, such as identity, class, category, weapons state, fuel status, threat level and intent, using the kinematic and attribute information from a variety of disparate sensors and sources. The Australian Defence Organisation is currently acquiring a number of capabilities, such as the Airborne Early Warning and Control, Air Defence Ground Environment and Joint Strike Fighter that will, or are expected to, provide some level of automation in this area.

The most critical and difficult problem in state estimation or tracking problems is that of data association. The use of attribute information in data association has the potential to provide greater discrimination and reduce association ambiguities. This paper addresses the joint kinematic and attribute data association problem, using a common probabilistic framework defined for both kinematic and attribute data using Bayesian Belief Networks (BBNs). This framework accommodates the uncertainty inherent in all sensor data, which is ignored in simple attribute gating techniques.

The paper is organised as follows. Following this introduction, an overview of relevant previous work is presented in Section 2, and a brief tutorial on BBNs is provided in Section 3. In Section 4, the joint kinematic

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and attribute data association algorithm is developed, with the results of the *Monte Carlo* analysis in Section 4, and conclusions in Section 6.

2 BACKGROUND

Tracking the dynamic or kinematic state of a target is well documented [1]. However, the dynamic behaviour of a target and information from other sensors and sources, such as secondary surveillance radar (SSR), electronic surveillance (ES), tactical data links and intelligence sources, can be used to estimate other attributes of a target, such as its identity, class, threat level and intent. Two key challenges are to successfully combine the disparate information or data, and to handle the uncertainty or errors in the data. Bayesian and Dempster-Shafer are two approaches that are able to accommodate these challenges. Bayesian techniques use Bayesian probability theory to handle uncertainty, whereas Dempster-Shafer introduces the concepts of support and plausibility [2, 3]. Bayesian probability theory provides a common frame of reference for the kinematic and attribute variables, and has previously been exploited for joint tracking and classification [4, 5].

Bayesian belief networks (BBNs) are causal belief networks that model the dependencies between variables or network nodes using Bayesian probability [6]. The ability of BBNs to model both continuous and discrete variables, and the relationships between such variables, make them excellent candidates for developing Bayesian approaches to attribute tracking and fusion systems. Korpisaari and Saarinen [7] proposed a generalised Bayesian network structure with a many-dimensional association vector for applying attribute data in a Joint Probabilistic Data Association (JPDA) context. With Hautaniemi [8], these authors recognised how the dependencies between attributes generally produce non-singly connected networks for attributes that evolve over time. Chang and Fung [9] used a BBN to incorporate attribute information into a multiple hypothesis tracking algorithm. Krieg [10] showed how BBNs may be used as a basis for deriving the Kalman filter tracking algorithm and a joint kinematic and attribute nearest neighbours data association algorithm. He also developed an attribute estimation algorithm, which he applied to the target tracking and recognition application. In [11], he used BBNs to develop a joint tracking and classification solution.

3 OVERVIEW OF BAYESIAN BELIEF NETWORKS

A Bayesian belief network (BBN) is a causal network that is represented by a directed acyclic graph, where the nodes represent stochastic variables and the directed links or arcs represent the direct causal influences between the variables [12]. Bayesian calculus, in particular predetermined prior and conditional probabilities, is used to determine the posterior node probabilities from the data or evidence applied to the network. Although the network provides a complete probabilistic model of all the variables in a specific domain, its design is based on local interactions between variables that directly influence one another. Therefore, it is only necessary to determine the conditional probabilities for each variable [6]; a conceptually simpler task than defining the entire joint probability.

The *belief* or posterior probability of the state of each variable in a BBN is dynamically calculated from the static conditional probabilities and the propagation of evidence. When applied to the network, evidence is propagated in the direction of the causal links by π messages and against the direction of the links by λ messages. On receipt of a message from another node, a node will update its belief and propagate new messages to each node directly connected to it, thereby ensuring the evidence is propagated throughout the network. The belief at any node is the normalised product of the λ and π information at that node.

For simplicity, the following description of evidence propagation in BBNs is restricted to tree network structures. Unless stated otherwise, a node or variable is denoted by an uppercase alphabetic character, and its value is denoted by its lowercase equivalent.

Consider the propagation of evidence through the BBN in Figure 1. The evidence influencing the proposition $X = x$ is separated into two disjoint subsets, namely that introduced to X through the arcs between X and its

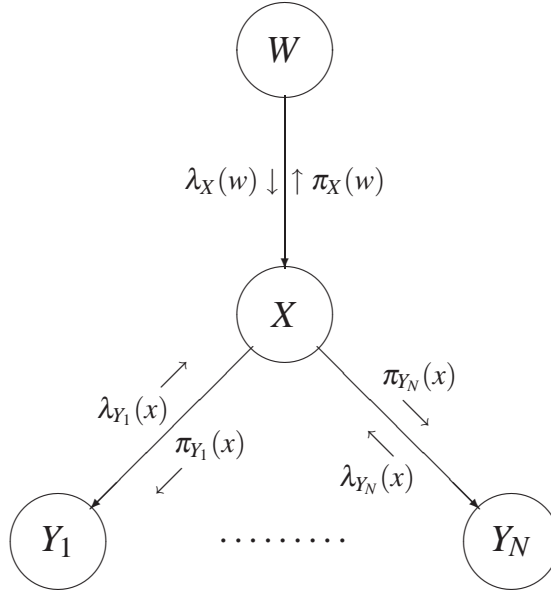


Figure 1. Evidence propagation in a BBN

children, Y_1, \dots, Y_N , and that introduced through the arc between X and its parent, W . The former is aggregated into the likelihood $\lambda(x)$, representing the *diagnostic* or *retrospective* support for the proposition $X = x$, and the latter the prior probability $\pi(x)$, representing the *causal* or *predictive* support for $X = x$. The belief of $X = x$ is then simply

$$\text{Bel}(x) = \alpha \pi(x) \lambda(x), \quad (1)$$

where α is a normalising constant.

For simplicity, and without loss of generality, it is assumed that all evidence is introduced into the BBN through leaf nodes. Then the retrospective support provided by the evidence on each leaf node Y_i , $i = 1, \dots, N$, is reflected by the message $\lambda(y_i)$, which takes the value $\delta_{y_i y'_i}$, if instantiated with y'_i , or some other value representing the probability that $Y_i = y_i$. This support is then propagated to X as

$$\lambda_{Y_i}(x) = \sum_{y_i} p(y_i | x) \lambda(y_i), \quad (2)$$

and combined with the support from the other children of X using

$$\lambda(x) = \prod_{i=1}^N \lambda_{Y_i}(x). \quad (3)$$

The retrospective support is then propagated to W according to

$$\lambda_X(w) = \sum_x p(x | w) \lambda(x). \quad (4)$$

The π messages propagate predictive support in the direction of the links. The support provided by the root node W is simply the prior probability of W , that is, $\pi(w) = p(w)$, and this is propagated to X using

$$\pi(x) = \sum_w p(x | w) \pi(w). \quad (5)$$

The propagation continues from X to the children of X using

$$\pi_{Y_i}(x) = \alpha \prod_{k=1 \setminus i}^N \lambda_{Y_k}(x) \pi(x) = \alpha \frac{\text{Bel}(x)}{\lambda_{Y_i}(x)}, \quad (6)$$

and

$$\pi(y_i) = \sum_x p(y_i | x) \pi_{Y_i}(x). \quad (7)$$

The belief at all nodes may now be calculated.

4 JOINT KINEMATIC AND ATTRIBUTE FUSION

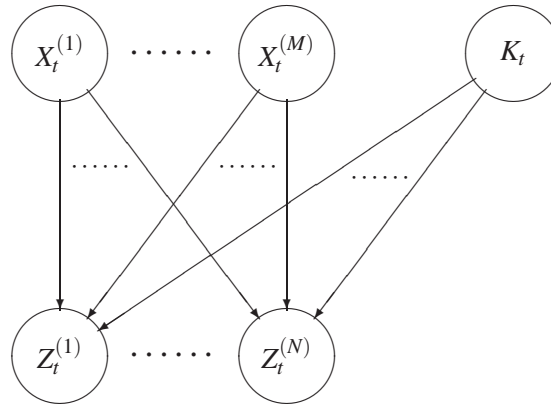


Figure 2. BBN for associating measurements to tracks

Consider the problem of associating N measurements at some time t to M tracks or other entities. Denoting the measurements as $z_t^{(n)}$, $n = 1, 2, \dots, N$, and the track states as $x_t^{(m)}$, $m = 1, 2, \dots, M$, and introducing an $N \times 1$ association vector, $k_t = (k_t^{(1)}, k_t^{(2)}, \dots, k_t^{(N)})^T$, $k_t^{(i)} \in \{1, 2, \dots, M\}$, where the value of the i^{th} element indicates the track to which the i^{th} measurement is associated, the problem becomes one of estimating the value of k_t . This may be represented by the BBN in Figure 2. Both the measurements and track states may contain both attribute and kinematic information, and the corresponding probabilities represent the joint probabilities of all the attribute and kinematic elements.

The BBN of Figure 2 is not singly connected, that is, it contains loops in the underlying Markov network. Therefore, the clustering approach [6, 13] is used here to produce the tree structure of Figure 3, where the clustered variable $A_t = \{X_t^{(1)}, X_t^{(2)}, \dots, X_t^{(M)}, K_t\}$. The conditional probabilities are now given as

$$p(z_t^{(n)} | A_t) = p(z_t^{(n)} | k_t, x_t^{(k_t^{(n)})}), \quad n = 1, 2, \dots, N. \quad (8)$$

From (1), the posterior probability, or belief, of A_t is given by

$$\text{Bel}(A_t) = \alpha \lambda(A_t) \pi(A_t). \quad (9)$$

The predictive support is simply the prior probability of A_t , namely

$$\pi(A_t) = p(A_t) = p(k_t) \prod_{m=1}^M p(x_t^{(m)}), \quad (10)$$

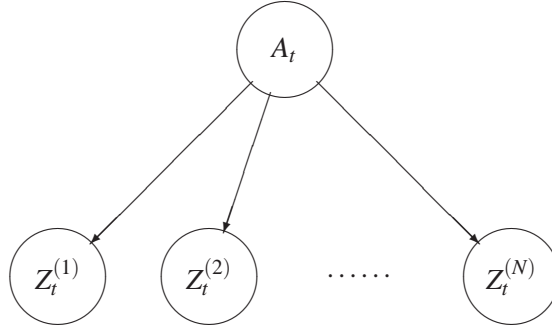


Figure 3. Cluster BBN for associating N measurements to M tracks

assuming that the track prior probabilities are independent, which is valid if it is assumed that a measurement can only be associated with a single track.

Denoting the known value of $z_t^{(n)}$ as $z_t^{(n)'}$,

$$\lambda(z_t^{(n)}) = \delta_{z_t^{(n)} z_t^{(n)'}} , \quad (11)$$

where $\delta_{z_t^{(n)} z_t^{(n)'}}$ equals 1 when $z_t^{(n)} = z_t^{(n)'}$ and 0 otherwise. Using (2) and (8), the retrospective support to A_t from the n^{th} measurement becomes

$$\lambda_{Z_t^{(n)}}(A_t) = p\left(z_t^{(n)'} \mid k_t, x_t^{(k_t^{(n)})}\right) , \quad (12)$$

and, from (3), the support for A_t from all measurements is

$$\lambda(A_t) = \prod_{n=1}^N p\left(z_t^{(n)'} \mid k_t, x_t^{(k_t^{(n)})}\right) . \quad (13)$$

Invoking (9) with (10) and (13) gives

$$\text{Bel}(A_t) = \alpha p(k_t) \prod_{m=1}^M p\left(x_t^{(m)}\right) \prod_{n=1}^N p\left(z_t^{(n)'} \mid k_t, x_t^{(k_t^{(n)})}\right) . \quad (14)$$

The belief of k_t may now be found by marginalising A_t , that is,

$$\text{Bel}(k_t) = \alpha p(k_t) \sum_{x_t^{(1)}} \sum_{x_t^{(2)}} \cdots \sum_{x_t^{(M)}} \prod_{m=1}^M p\left(x_t^{(m)}\right) \prod_{n=1}^N p\left(z_t^{(n)'} \mid k_t, x_t^{(k_t^{(n)})}\right) , \quad (15)$$

which may be rewritten

$$\text{Bel}(k_t) = \alpha p(k_t) \prod_{m:m \in k_t} \sum_{x_t^{(m)}} p\left(x_t^{(m)}\right) \prod_{n:k_t^{(n)}=m} p\left(z_t^{(n)'} \mid x_t^{(m)}\right) , \quad (16)$$

where α is a normalising constant. Using the most probable value as the best estimate for the association vector, α may be ignored, as the solution is simply

$$\hat{k}_t = \arg \max_{k_t} p(k_t) \prod_{m:m \in k_t} \sum_{x_t^{(m)}} p\left(x_t^{(m)}\right) \prod_{n:k_t^{(n)}=m} p\left(z_t^{(n)'} \mid x_t^{(m)}\right) . \quad (17)$$

Of particular interest is the prior distribution of k_i . If all permutations of the association vector are equiprobable, then the solution under linear and Gaussian assumptions is equivalent to the nearest neighbours association algorithm for both kinematic and attribute data. However, zeroing the prior probability of all the permutations of the association vector that associate more than one measurement from any sensor to one same target constrains the solution and the result is a global nearest neighbours algorithm for both kinematics and attributes.

5 RESULTS

The association algorithm of Section 4, with the constraint that each target can only produce one measurement from each sensor, is applied to the tracking and identification problem for crossing targets. Probabilistic gating is used to eliminate low probability associations. Measurements are simulated from two sensors, namely a secondary surveillance radar (SSR) returning range, azimuth and identity, and an Electronic Surveillance (ES) sensor returning azimuth and platform class, which is related to identity. Kinematic and identity updates are performed by the Extended Kalman Filter (EKF) and the identity update algorithm of [10], respectively. Two cases are considered, one with association based only on kinematic data, and the other using both kinematic and attribute data for association.

Figures 4 and 5 show the track locations for a single run for kinematic only association and joint attribute and kinematic association, respectively. The track positions are indicated by solid lines, and the ground truth by dotted lines. The SSR position measurements from each target are shown, where the ‘+’ represents those from one target, and the ‘o’ those from the other target.

Frequent track swaps, as illustrated by Figure 4, are observed when only kinematic data is used for data association. The use of both kinematic and attribute data overcomes this problem. This is reflected in the association accuracy results presented in Table 1, where the percentage of measurements from each target that are associated with each track is presented for both the SSR and ES sensors. Perfect association would result in all measurements from target 1 associated with track 1, and all measurements from target 2 associated with track 2. The results for both sensors reflect the difficulty of associating reports to closely spaced entities using only kinematic data. The additional discrimination introduced by the attribute data provides the observed improvement in performance of the joint association over the kinematic only association.

This example demonstrates the advantage of using both attribute and kinematic data for data association. This is equally applicable to other data fusion applications, where other attribute information may be involved.

Table 1. Association accuracies for kinematic and joint kinematic and attribute association

Sensor	Target	Track	Assoc. Accuracies (%)	
			Kinematic	Joint
SSR	1	1	86	99
		2	13	0.05
	2	1	13	0.05
		2	85	98
ES	1	1	58	71
		2	41	27
	2	1	42	28
		2	57	71

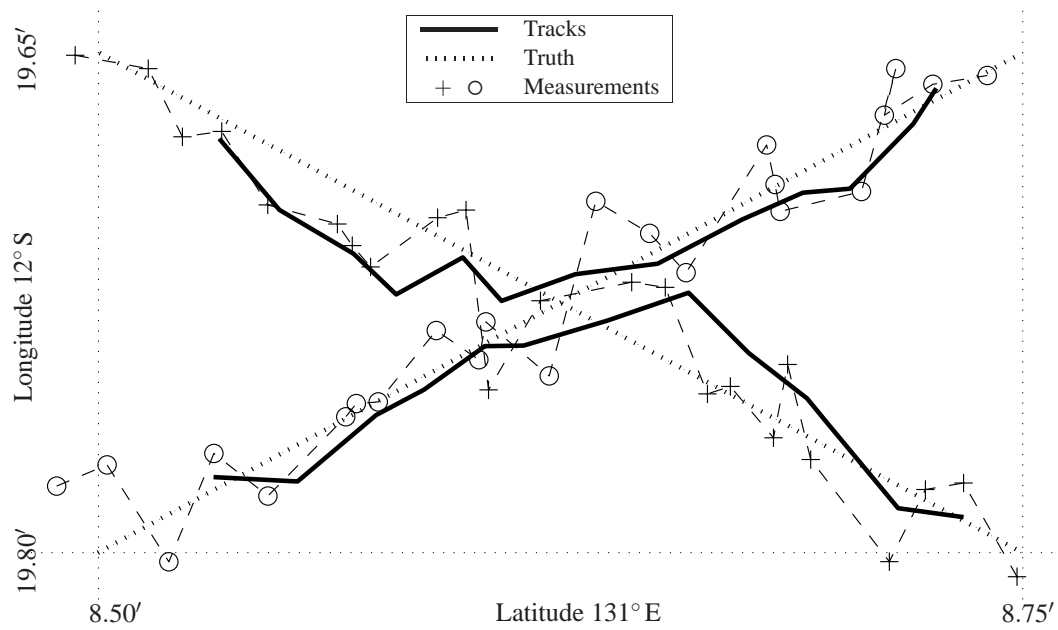


Figure 4. Track location using kinematic only association

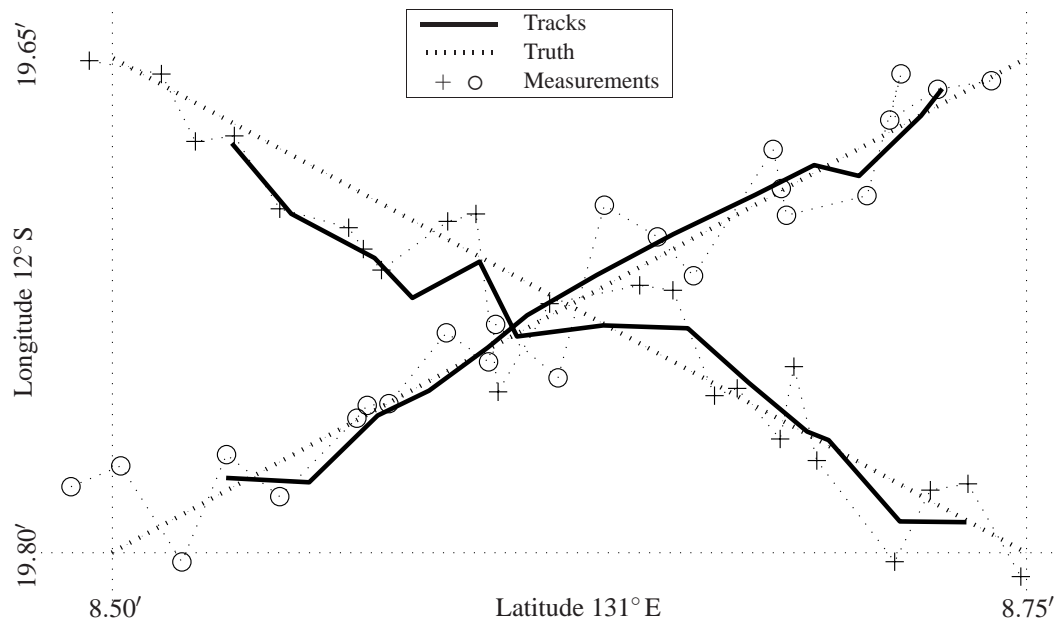


Figure 5. Track location using joint kinematic and attribute association

6 CONCLUSIONS

Accurate data association is a necessary requisite for the fusion of multi-source multi-target information. A joint kinematic and attribute data association algorithm that incorporates data uncertainty has been developed using a BBN framework. Significant improvement in association accuracy over kinematic only association has been demonstrated through simulation.

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Overview

- Problem
- Bayesian Belief Networks
- Algorithm Development
- Results
- Conclusions

Problem

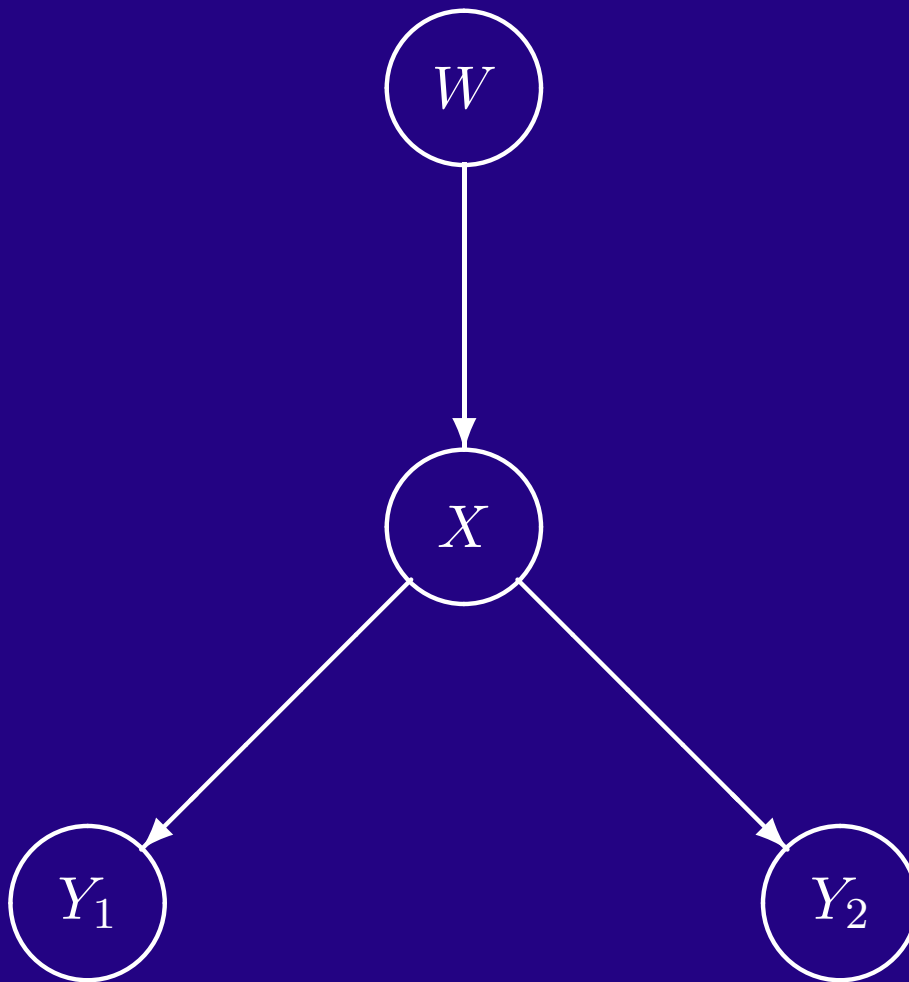
- Attribute data or information
 - Multiple disparate sensors and sources
 - Contribution to automated situational picture
- Data association
 - Considered most challenging problem
 - Attributes may provide greater discrimination
 - Need to consider uncertainty

Bayesian Belief Networks

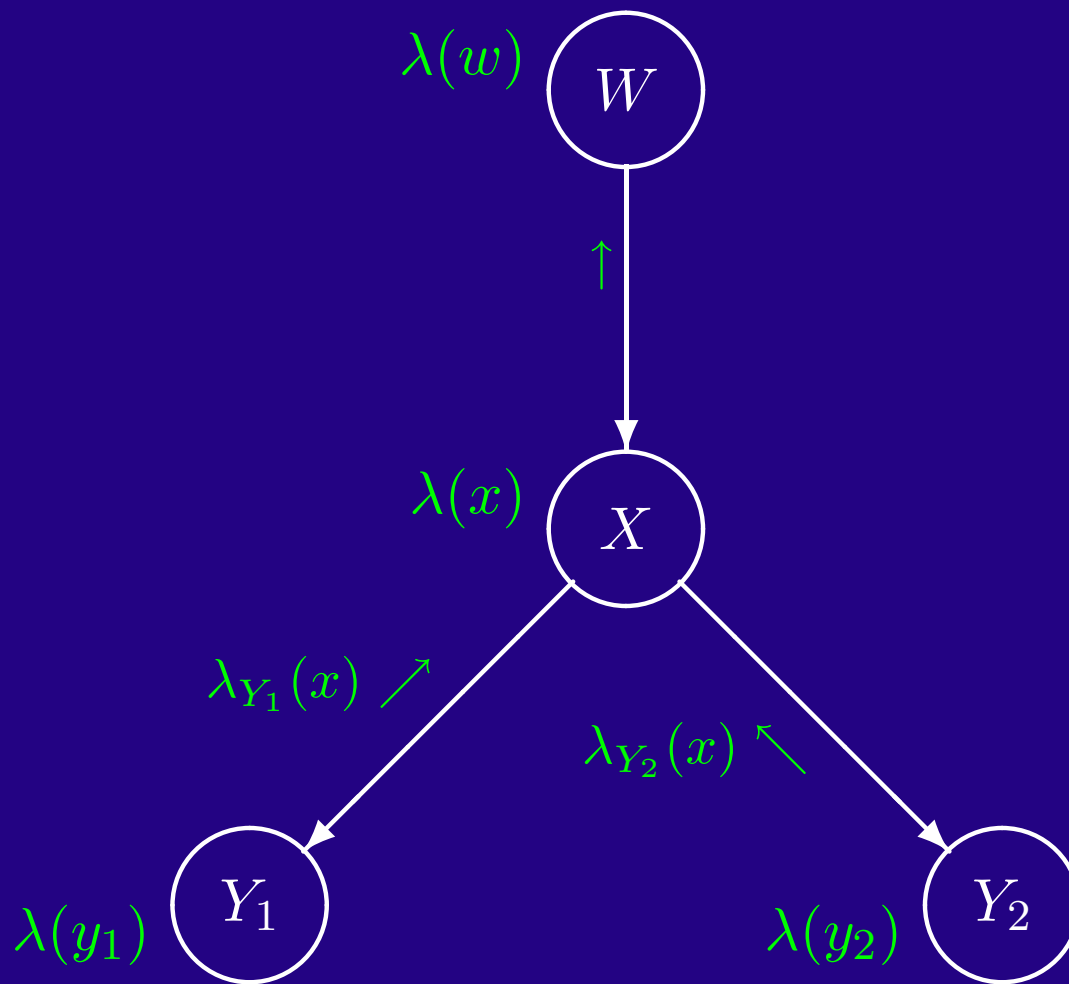
Causal network

- Continuous and discrete variables
- Bayesian calculus
- Uncertainty
- Complete probabilistic model of all variables
- Only need to define local interactions
- Evidence propagation through network

Evidence Propagation in a BBN



Evidence Propagation in a BBN



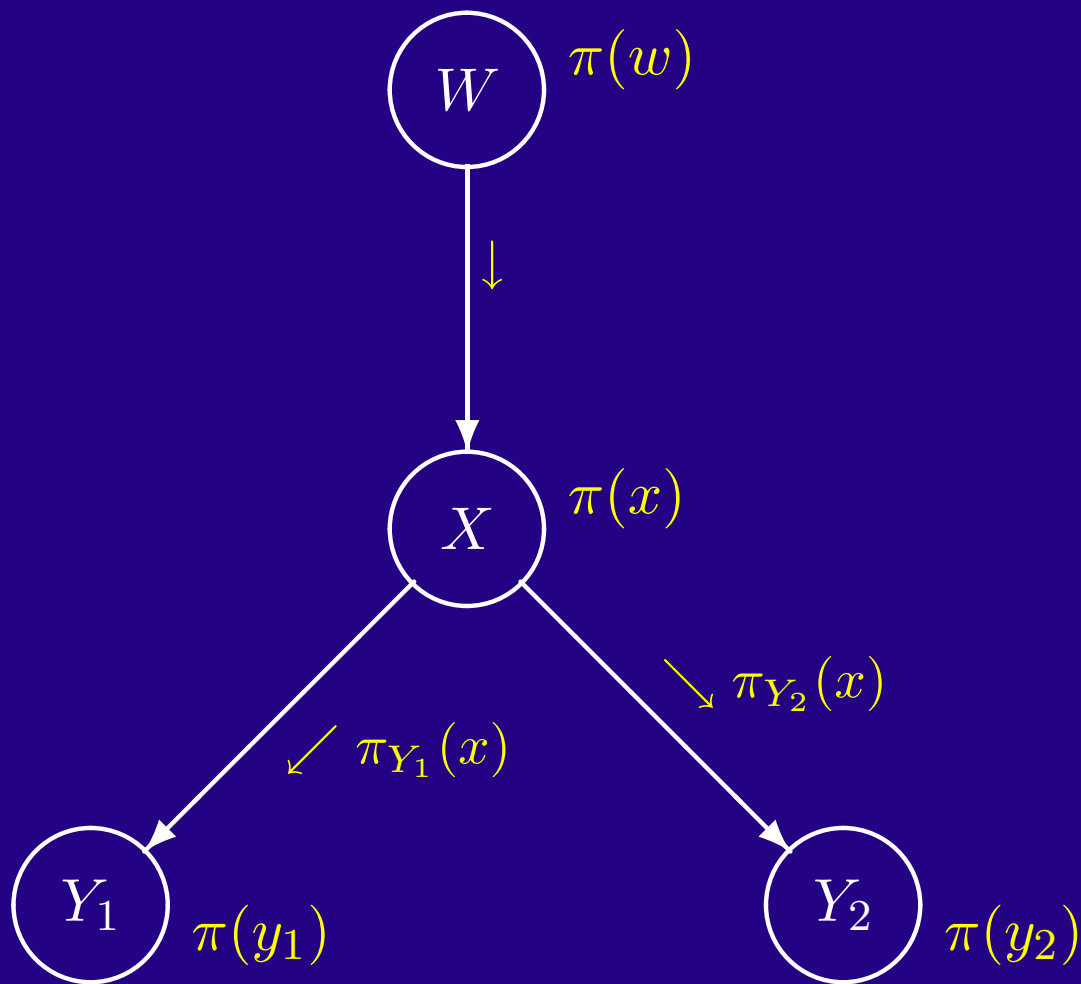
$$\lambda(y_i) = \delta_{y_i y'_i}$$

$$\lambda_{Y_i}(x) = \sum_{y_i} \mathbf{p}(y_i | x) \lambda(y_i)$$

$$\lambda(x) = \lambda_{Y_1}(x) \lambda_{Y_2}(x)$$

$$\lambda(w) = \sum_x \mathbf{p}(x | w) \lambda(x)$$

Evidence Propagation in a BBN



$$\pi(w) = \mathbf{p}(w)$$

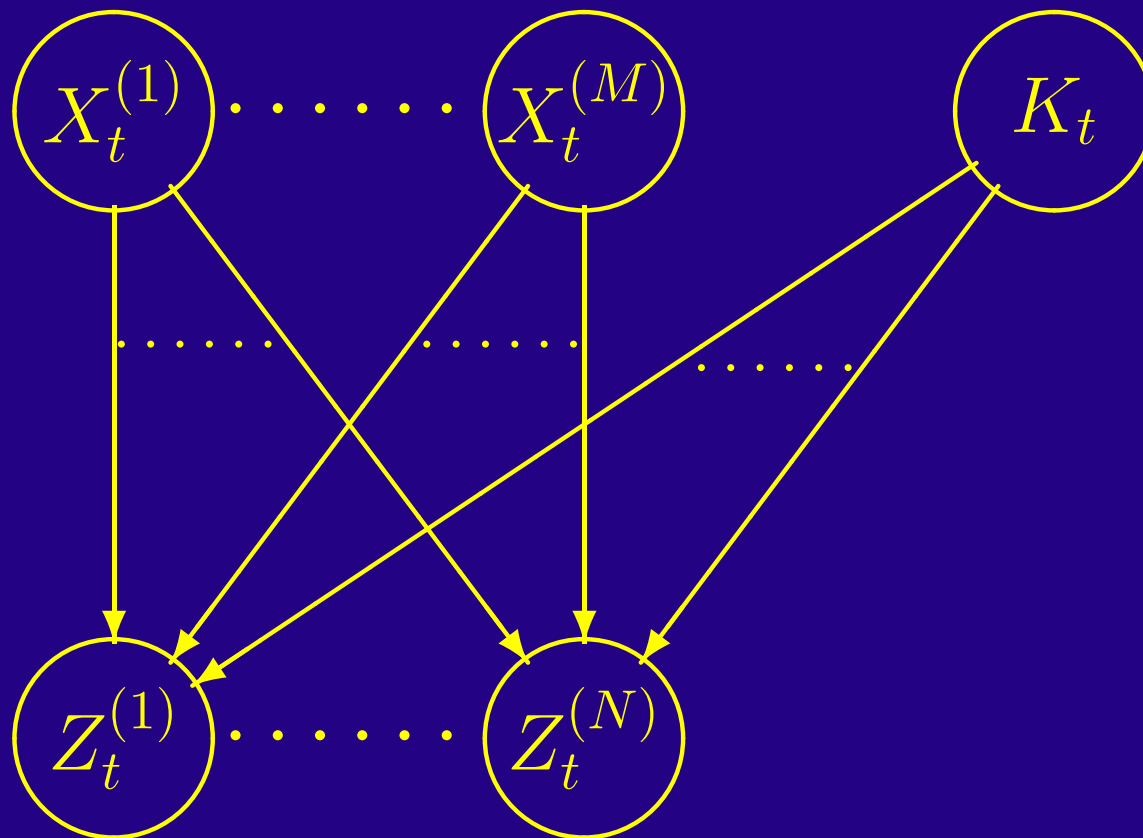
$$\pi(x) = \sum_w \mathbf{p}(x | w) \pi(w)$$

$$\pi_{Y_1}(x) = \lambda_{Y_2}(x) \pi(x)$$

$$\pi(y_i) = \sum_x \mathbf{p}(y_i | x) \pi_{Y_i}(x)$$

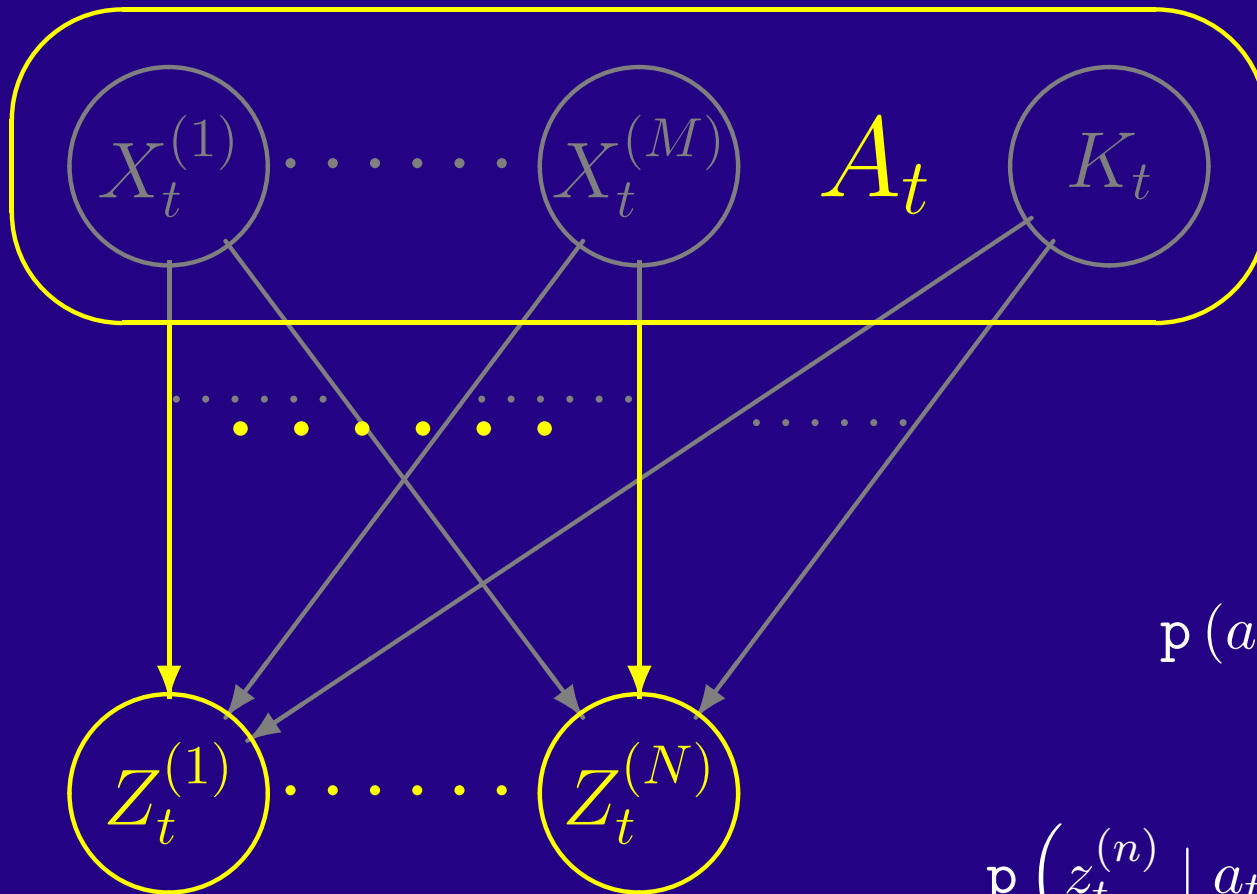
Algorithm Development

Associating Measurements to Tracks



Problem: Loops in underlying Markov network

Associating Measurements to Tracks



$$p(a_t) = p(k_t) \prod_{m=1}^M p(x_t^{(m)})$$

$$p(z_t^{(n)} | a_t) = p(z_t^{(n)} | x_t^{(k_t^{(n)})})$$

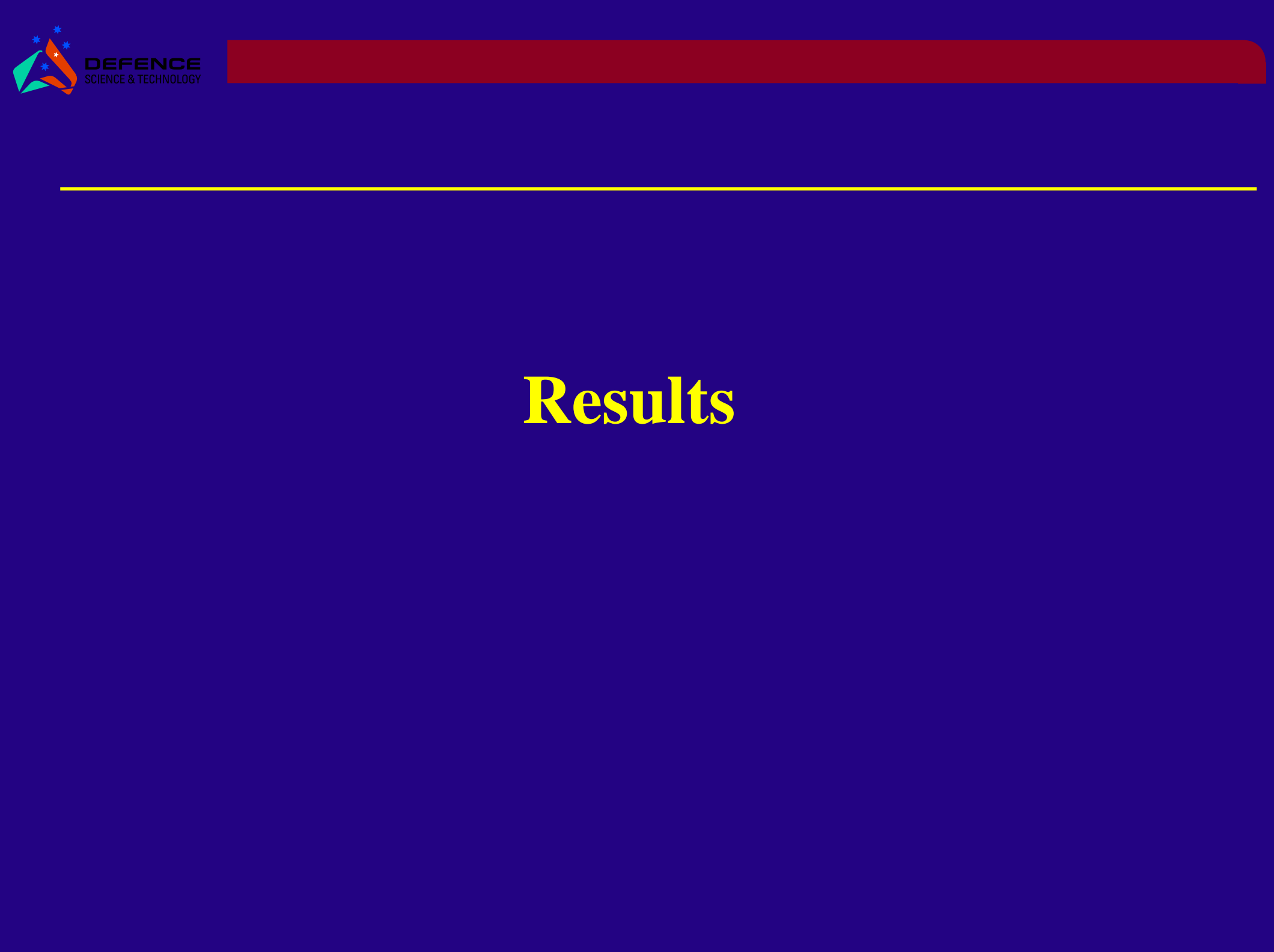
Algorithm

Posterior Probability:

$$\text{Bel}(k_t) = \alpha p(k_t) \prod_{m: m \in k_t} \sum_{x_t^{(m)}} p(x_t^{(m)}) \prod_{n: k_t^{(n)} = m} p(z_t^{(n)' | x_t^{(m)})}$$

Best estimate:

$$\hat{k}_t = \arg \max_{k_t} \text{Bel}(k_t)$$

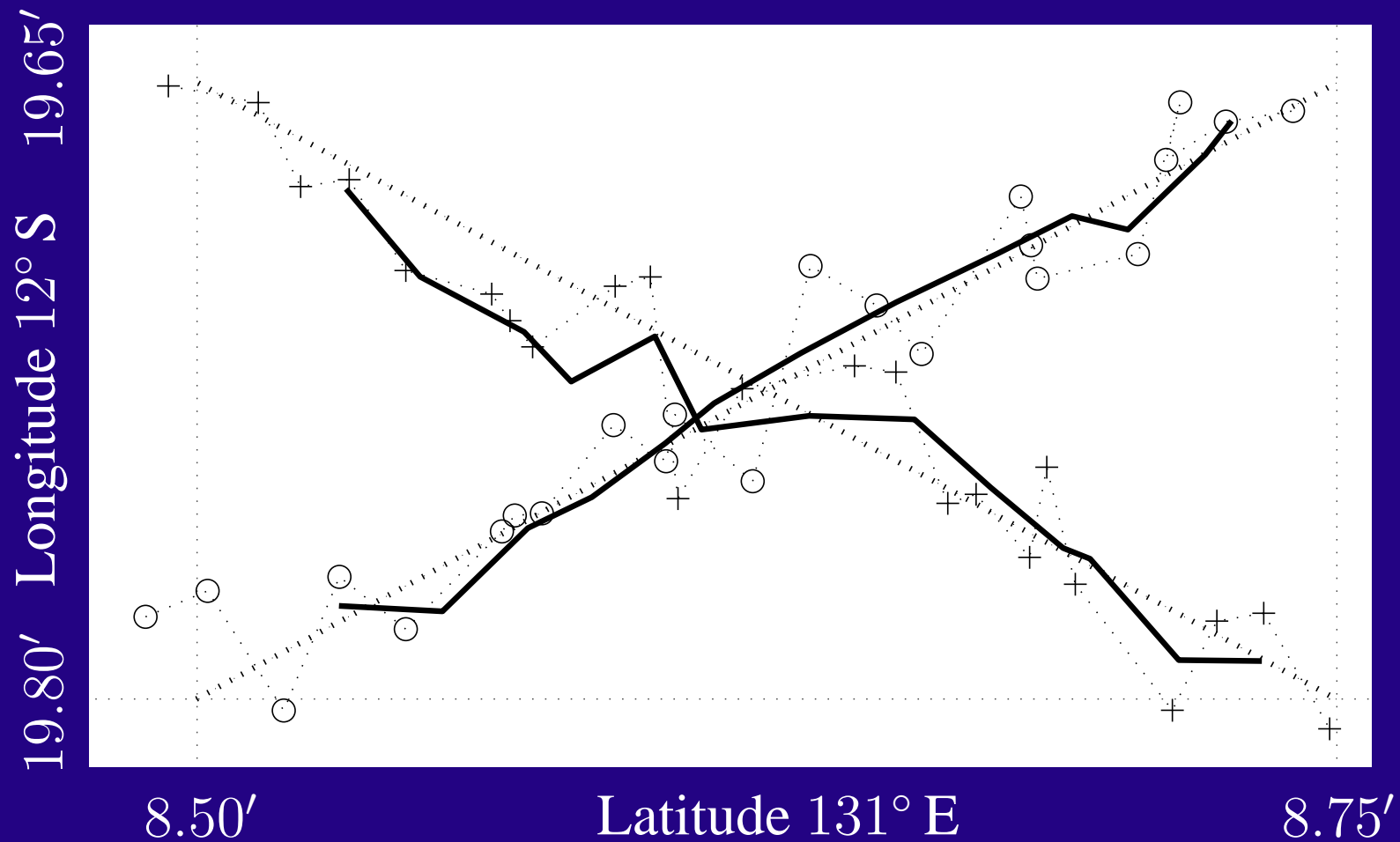


Results

Simulations

- Two targets crossing
- Two sensors:
 - Secondary Surveillance Radar
 - Electronic Support (ES)
- Association constrained to one measurement / target / sensor
- Probabilistic gating applied prior to association
- Kinematic state update using EKF
- ID update using algorithm of [Krieg, IDC2002]
- Simulations for both kinematic only and joint kinematic / attribute association

Track Position Estimates



Association Accuracies

Sensor	Target	Assoc. Accuracies (%)	
		Kinematic	Joint
SSR	1	86	99
	2	85	98
ES	1	58	71
	2	57	71

Conclusions

- Accurate data association prerequisite for fusion.
- Developed joint kinematic & attribute association algorithm that:
 - is based on BBN framework;
 - incorporates uncertainty;
 - improves accuracy over kinematic only.
- May be applied to higher level applications.